Comparison of vegetation water contents derived from shortwave-infrared and passive-microwave sensors over central Iowa

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ABSTRACT
Retrieval of soil moisture content using the vertical and horizontal polarizations of multiple frequency bands on microwave sensors can provide an estimate of vegetation water content (VWC). Another approach is to use foliar-water indices based on the absorption at shortwave-infrared wavelengths by liquid water in the leaves to determine canopy water content, which is then related to VWC. An example of these indices is the normalized difference infrared index (NDII), which was found to be linearly related to canopy water content using various datasets, including data from the Soil Moisture Experiments 2002 and 2005 in central Iowa. Here we compared independent estimates of VWC from WindSat to Moderate resolution Imaging Spectroradiometer (MODIS) NDII over central Iowa from 2003 to 2005. Results showed that there was a linear relationship between the MODIS and WindSat estimates of VWC, although WindSat-retrieved VWC was greater than MODIS-retrieved VWC. WindSat and MODIS have different satellite overpass times and in most climates we expect VWC to vary over a day due to transpiration and plant water stress. However, a sensitivity analysis indicated that the diurnal variation of VWC should not have a significant affect on retrievals of VWC by either method. The results of this study indicated that soil moisture retrievals from microwave sensors may be improved using VWC from optical sensors determined by foliar-water indices and classifications of land cover type.

1. Introduction

Determination of soil moisture content by microwave remote sensing is important for quantifying the global energy, water and carbon cycles (Jackson & Schmugge, 1991; Jackson, 1993; Njoku et al., 2003; Jackson et al., 2010). Vegetation water content (VWC, kg m^{-2}), which we define here as the liquid water in stems and foliage, is one of the important parameters that must be accounted for in the retrieval of soil moisture content using passive microwave radiometers (Jackson & Schmugge, 1991; Jackson, 1993; Njoku et al., 2003; Van de Griend & Wigneron, 2004; Jackson et al., 2010).

Dual-polarization, multi-frequency data from passive-microwave radiometers also provide an estimate of VWC during retrievals of soil moisture content. The retrieval algorithm developed for the Coriolis mission's WindSat uses the horizontal and vertical polarizations for channels at 10, 18.7 and 37 GHz to solve simultaneously for soil moisture content, VWC, surface temperature, and surface roughness (Li et al., 2010). These channels are also on NASA Aqua's Advanced Microwave Scanning Radiometer (AMSR-E) and the Tropical Rainfall Monitoring Mission (TRMM) Microwave Imager (TMI). The WindSat retrievals for soil moisture content have been validated using data from a few field campaigns, in order to determine whether the data products met the requirements for science and operational applications (Li et al., 2010). However, WindSat retrievals for VWC have not been validated.

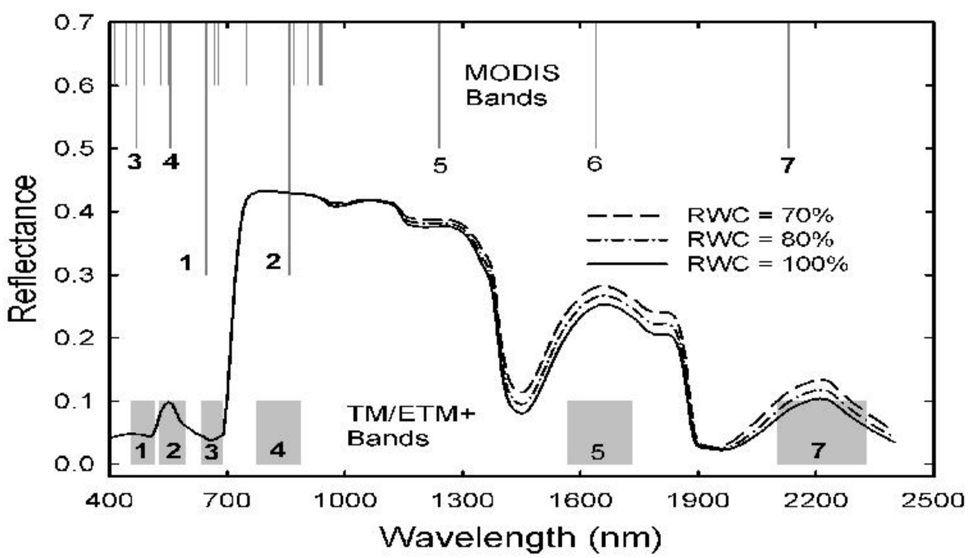

Fig.1. Leaf spectral reflectances from PROSPECT model simulations for three leaf relative water contents (RWC). RWC of 100% is full turgor and RWC of 70% is wilting for most species. Leaf water contents (LWC) of 0.14, 0.17 and .20 kg m^{-2} were used for RWC of 70, 85, and 100%, respectively. Also shown are the bands for MODIS and Landsat TM/ETM+. For the MODIS bands, bands 1 and 2 have 250-m spatial resolution, bands 3-7 have 500-m spatial resolution, and the other bands have 1000-m spatial resolution. The normalized difference infrared index (NDII) was calculated using MODIS bands 2 and 6 and TM/ETM+ bands 4 and 5.

Red/near-infrared vegetation indices, such as the normalized difference vegetation index (NDVI), are related to several different canopy attributes including leaf area index (LAI), fractional vegetation cover, and absorbed photosynthetically active radiation (Tucker, 1979; Myneni et al., 2002). These indices can explain some of the variation among soil moisture retrieval algorithms for passive microwave sensors (Owe et al., 1988; Burke et al., 2001; Doubková & Henebry, 2006). However, red/near-infrared indices have limited capabilities in estimating VWC (Jackson et al., 2004; Chen et al., 2005).

Liquid water in leaves has strong absorption features at near-infrared and shortwave infrared wavelengths (Fig. 1), which can be used to determine leaf water content (LWC, kg m^{-2}). In the literature, LWC is also called leaf equivalent water thickness (Allen et al., 1969; Hunt & Rock, 1989). The product of LWC and LAI is the canopy water content (CWC, kg m^{-2}). Foliar-water indices based on water absorption bands are strongly related to LWC and CWC (Tucker, 1980; Hunt & Rock, 1989; Hunt, 1991; Peñuelas et al., 1993; Gao, 1996; Zarco-Tejada et al., 2003; Jackson et al., 2004; Chen et al., 2005; Clevers et al., 2008; Vohland, 2008; Yilmaz et al., 2008a, 2008b; Wang et al., 2008). There are also other algorithms for CWC, which are based on model inversions or artificial neural networks (Riaño et al., 2005; Cheng et al., 2006, 2008; Trombetti et al., 2008), but foliar-water indices have been studied in much more detail.

Stem mass, which is not directly observed with optical sensors, may be estimated using allometric relationships between leaf and stem dry mass. Because stems are required for both support and water transport, allometric equations are hypothesized to have a physical basis (Enquist & Niklas, 2002; Niklas & Enquist, 2002). The general allometric equation is:

$$M_L = \alpha \, M_S^{\,\beta} \tag{1}$$

where M_L is the leaf dry mass, M_S is the stem dry mass, and α and β are the allometric coefficients (Niklas & Enquist, 2002). It is then assumed that that Eq. 1 will also apply to leaf and stem fresh mass and hence to canopy and stem water contents. One theoretical value for all vascular plants is $\beta = 0.75$ (Enquist & Niklas, 2002; Niklas & Enquist, 2002); different land cover types are expected to have different α coefficients. If the allometric coefficients are known, then estimates of canopy water content from foliar-water indices may be used to estimate stem water content, and hence VWC.

Our ultimate goal is to incorporate VWC derived from optical sensors into retrieval algorithms for soil moisture content from WindSat, AMSR-E, and TRMM, in order to develop long-term multi-sensor data records (NRC, 2007, page 70). The method developed for estimating VWC from MODIS requires land cover information and CWC from foliar-water indices (Yilmaz et al., 2008b). Working towards the goal, we compared VWC retrieved from WindSat and the Moderate resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra satellite over central Iowa during the 2003 to 2005 growing seasons. Furthermore, a potential problem with determining VWC is that VWC varies over a day because of the dynamics between transpirational water loss and soil water uptake by vegetation, and varies over longer time steps because of plant water stress (Hunt et al., 1991). Therefore, the different satellite overpass times of WindSat and MODIS could create possible biases in estimating VWC from a combined algorithm. We assessed whether diurnal variations of CWC would affect foliar-water indices using simulations with leaf and canopy reflectance models.

2. Methods

2.1. Soil Moisture Experiments

The Soil Moisture Experiments 2002 (SMEX02) and 2005 (SMEX05) were conducted over the same region of central Iowa (Jackson et al., 2004; Yilmaz et al., 2008b). Leaves and stems of corn and soybean were collected from sample plots during both campaigns. LWC was determined from the difference of fresh and dry weights divided by leaf area. CWC was calculated from the product of average LWC and LAI. Stem water content was calculated from the difference of stem fresh and dry weights, multiplied by plant density. VWC is the sum of CWC and stem water content. Although useful in the context of VWC, the SMEX02 occurred the summer before the launch of WindSat on January 6, 2003 and therefore, cannot be compared to microwave retrievals.

Foliar-water indices contrast radiation absorption by water at shortwave-infrared wavelengths with radiation scattering by foliage at near-infrared wavelengths (Hunt & Rock, 1989); many optical sensors have a channel at about 1.65 μm wavelength. The Normalized Difference Infrared Index (NDII) was calculated:

$$NDII = (R_{0.85} - R_{1.65})/(R_{0.85} + R_{1.65}) \quad (2)$$

where: $R_{0.85}$ and $R_{1.65}$ are reflectances at 0.85 and 1.65 μm, respectively (Hardisky et al., 1983). ACORN version 5.5 (ImSpec LCC, http://www.imspec.com) was used to calculate land-surface reflectances from radiance data of Landsat 5 Thematic Mapper (TM), Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and the Indian Resourcesat-1 Advanced Wide Field Sensor (AWiFS). From the satellite data, $R_{0.85}$ and $R_{1.65}$ were obtained for each sample plot to determine the relationship between NDII and CWC over the growing season (Yilmaz et al., 2008b). In order to make the relationship more general, data from the literature for grasslands (Ceccato et al., 2002; Davidson et al., 2006) and the Soil Moisture Experiment 2004 (Yilmaz et al., 2008a) were included. An ordinary least-squares linear regression provided the best fit to NDII and CWC data.

2.2. MODIS and land cover data

The MOD09A1 8-day level-3 500-m surface reflectance data (Collection 5) were obtained for the years 2003, 2004 and 2005 from the NASA Land Processes Distributed Active Archive Center located at the USGS Eros Data Center (Sioux Falls, SD). NDII was calculated from MODIS band 2 (0.841-0.876 μm), and MODIS band 6 (1.628-1.652 μm) using Equation 2. MODIS NDII was used to calculate CWC for each MODIS pixel using an empirical relationship derived from the field data described above.

The USDA National Agricultural Statistics Service's (NASS) 2003, 2004, and 2005 Cropland Data Layers (Mueller & Seffrin, 2006) were acquired for Iowa with a 30-m spatial resolution. The mean field size in central Iowa is 20.5 ha (Alan J. Stern, personal communication), so the land cover type for each MODIS pixel was determined by the majority of the 30-m pixels from the annual Cropland Data Layers.

Allometric equations relating VWC and CWC (Equation 1) were developed for corn and soybean using data from SMEX02 and SMEX05 (Yilmaz et al., 2008b). For other land cover types, there were not enough data to determine allometric equations. For woodlands, we used the average value of VWC from the SMEX05 experiment, 5 kg m^{-2} (Yilmaz et al., 2008b). For pasture cover classes, we assumed that VWC equaled CWC, which is appropriate for grasses.

VWC values for each MODIS pixel in a WindSat footprint (about 2800 pixels) were averaged to obtain the VWC of the footprint.

2.3. WindSat data

The WindSat land algorithm retrieves soil moisture, VWC and land surface temperature simultaneously using a maximum-likelihood function with the dual-polarized 10, 18, and 37 GHz WindSat channel measurements (Li et al., 2010). The 6 GHz channels were not used because of radio-frequency interference over the US and other regions (Li et al., 2004). For a land surface with a layer of vegetation, surface emissivity for polarization p (e_{bp}) can be approximated using the tau-omega model (Jackson & Schmugge, 1991; Jackson, 1993):

$$e_{bp} = T_{bp}/T_s = e_{sp}\exp(-\tau_c) + (1-\omega_p)(1-\exp(-\tau_c))(1+r_{sp}\exp(-\tau_c)) \quad (3)$$

where: T_{bp} and T_s are the brightness temperature for polarization p and effective surface temperature, respectively, assuming that the soil surface and vegetation temperatures are approximately equal; e_{sp} and r_{sp} (= $1 - e_{sp}$) are the soil emissivity and reflectivity for polarization p, respectively; ω_p is the single scattering albedo for polarization p (empirically accounts for the scattering and emission properties of vegetation canopies); and τ_c is the vegetation optical depth. The first term in Eq. 3 is the soil emission attenuated by vegetation and the second term is the emission from vegetation. Vegetation optical depth (τ_c) is assumed to be linearly related to VWC:

$$\tau_c = b\ \mathrm{VWC}/\cos\theta \quad (4)$$

where: θ is the look angle and b is an attenuation parameter that depends on vegetation structure, vegetation dielectric properties, and frequency (Jackson, 1993; van de Griend & Wigneron, 2004).

The soil moisture retrievals using the tau-omega model have been validated using multi-temporal and multi-spatial data derived from soil moisture climatology, in situ observations, and precipitation (Jackson et al., 2010). Validations of WindSat VWC retrievals to date have been comparisons of phenology with AVHRR NDVI data, both spatially at global scales and temporally for a number of selected validation sites (Li et al., 2010).

WindSat spaceborne polarimetric microwave radiometer data were obtained over the period from the beginning of May to the beginning of August for 2003 and 2004, to focus on the crop growth period. Due to an instrument malfunction during 2005, data were acquired only from late June to the beginning of August. Brightness temperatures for three non-overlapping footprints (average 30 km radius) were extracted over central Iowa.

Table 1. Initial WindSat retrieval parameters by frequency for vegetation water content. The vegetation single-scattering albedo for horizontal polarization (ω_h) and vertical polarization (ω_v) are used in Equation 3, whereas the vegetation attenuation parameter (b) is used in Equation 4.

Frequency (GHz)	ω_h	ω_v	b (m^2 kg^{-1})
10.7	0.046	0.042	0.160
18.7	0.031	0.030	0.193
37	0.036	0.035	0.244

Because high VWC obscures emission from the soil surface, vegetation ω_h and ω_v (Table 1) were derived using the brightness temperatures at each frequency for a 1° by 1° grid cell, which consisted of a dense tropical rain forest located in the Democratic Republic of the Congo (0.5° N and 14.3° E). This approach was used to determine retrieval parameters for the Scanning Multichannel Microwave Radiometer (SMMR) and AMSR-E (Njoku and Li, 1999; Njoku and Chan, 2006). The instrument calibration errors were lumped into the model parameters, and thus the algorithm needs to be re-parameterized when instrument calibrations change.

The attenuation parameter for microwave radiation through vegetation (b, Equation 4) was also determined empirically using the brightness temperature polarization ratios [$(T_{bv} - T_{bh})/(T_{bv} - T_{bh})$] for various frequencies (Van de Griend and Wigneron, 2004; Njoku and Chan, 2006). Brightness temperatures for a large region with variable amounts of vegetation (central to northern Africa, 8° N to 16° N and 18° E to 30° E) and with uniformly dry soil were used to calculate the polarization ratios for the three frequencies (Table 1). The b parameter was not determined using ground VWC data, so comparisons of VWC from MODIS and WindSat retrievals were a unique opportunity to perform a calibration *in situ* at satellite footprint scales.

2.4. PROSPECT and SAIL model simulations

Simulations of leaf spectral reflectance and transmittance were made using the PROSPECT model, Version 4 (Jacquemoud et al., 1996; Feret et al., 2008; Jacquemoud et al., 2009). The leaf structure parameter N was set at 1.5; Haboudane et al. (2004) found that average N was 1.55 for corn and soybean and leaves. Leaf chlorophyll content was 0.45 mg m^{-2} and the dry matter content was 50 g m^{-2} (0.045 µg cm^{-2} and 0.005 g cm^{-2}, respectively). The range of LWC for corn and soybean during SMEX05 was 0.11 to 0.32 kg m^{-2} (unpublished data), so LWC was set at 0.2 kg m^{-2} (0.02 g cm^{-2}), which was close to the median value. To determine how either plant water stress or diurnal variations in LWC caused by transpiration would affect CWC, LWC was varied from 0.2 kg m^{-2} for leaves at full turgor (100% relative water content) to 0.14 kg m^{-2} (70% relative water content), at which point leaves are generally wilted (Hunt et al., 1991). The outputs from the PROSPECT model (Fig. 1) were used as inputs to the Scattering by Arbitrarily Inclined Leaves (SAIL) model (Verhoef, 1984). LAI from 0.01 to 4 were selected for the simulations and a spherical leaf angle distribution was assumed. The spectral reflectance of soil affects the value of vegetation indices for a given CWC (Zarco-Tejeda et al., 2003), so reflectance spectra under moist and dry conditions of three soils were obtained from Daughtry (2001) and used in the SAIL model simulations. The soil types were Barnes (coarse-loamy, mixed Udic Haploboroll from Morris, MN), Codorus (fine-loamy, mixed mesic, Fluvaquentic Dystrochrept from Beltsville, MD), and Othello (fine-silty, mixed mesic Typic Ochraquult from Salisbury, MD).

3. Results and Discussion

3.1. Canopy and vegetation water contents

There was a highly-significant linear relationship [P(type I error) < 0.0001] between CWC and NDII (Fig. 2). Furthermore, there was no significant difference ($P > 0.05$) between NDII and CWC among the various datasets using dummy variable regressions (Chatterjee & Hadi, 2006). The root mean square error (RMSE) was 0.09 kg m^{-2} (Fig. 2), whereas the maximum difference in leaf water content (LWC) expected for a 30% difference in relative water content (from 100% or full turgor to 70% or the wilting point) was only 0.06 kg m^{-2} (Fig. 1). The RMSE is larger than the maximum expected difference of leaf water content, changes in reflectance at shortwave-infrared wavelengths is not sufficiently responsive to detect either plant water stress or water loss from transpiration at the leaf scale (or at LAI < 2.0). Hunt & Rock (1989) reached this same conclusion using the Moisture Stress Index (= $R_{1.65}/R_{0.85}$).

Over the course of a day, there is little change in LAI, so variation in CWC is due to variation in LWC, which is generally highest during the early morning when transpiration rates and the amount of water stress are low (Hunt et al., 1991). Furthermore, LWC is generally lowest around midday, when either the transpiration rate is high (at low water stress) or the amount of water stress is large (with low transpiration rate). The Terra and Aqua MODIS daytime overpass times are 10:30 and 13:30, respectively, and are relatively close to solar noon. Thus, CWC from NDII may be smaller than the RMSE of 0.09 kg m^{-2}, so diurnal variation in CWC may not be detectable from MODIS. Furthermore, SAIL model simulations indicate the response of NDII was saturated between a CWC from 4 to 5 kg m^{-2} (results not shown), so large diurnal changes in CWC (diurnal changes of LWC multiplied by large LAI) may not be detectable using NDII even with different satellite overpass times. Inversion of leaf and canopy models (Cheng et al., 2006; Trombetti et al., 2008) may be more successful at detecting water stress with low LWC, because both LAI and LWC are retrieved, thus changes in LWC are determined separately from changes in CWC. Because the objective in this study is to estimate total vegetation water content (VWC), not just CWC, the linear relationship between NDII and WC (Fig. 2) indicates that NDII is related to plant growth over time.

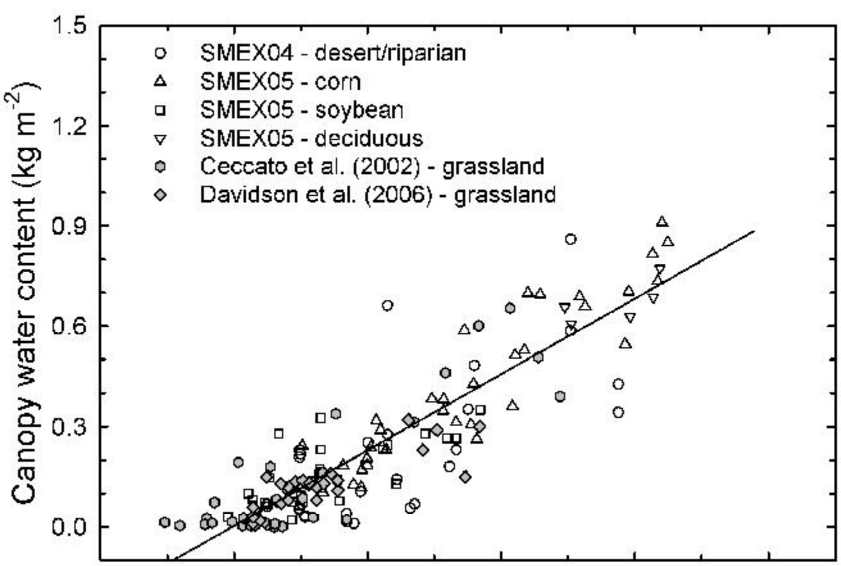

Fig.2. Relationship of canopy water content (CWC) with the Normalized Difference Infrared Index (NDII). The line is the equation from a linear regression, CWC = 0.23 + 1.18 NDII, which has an RMSE of 0.091 kg m^{-2}, an R^2 of 0.847, and the P (type I error) < 0.0001. The individual datasets were not significantly different (P > 0.05) from the overall regression line.

SAIL model simulations were used to determine the sensitivity of foliar-water indices for LAI, leaf angle distributions, sun-target-sensor geometries, and soil background reflectances (Goward & Huemmrich, 1992; Zarco-Tejada et al., 2003; Jacquemoud et al., 2009). Soil background reflectance is highly variable, and strongly affects NDII (Fig. 3). The regression equation from Fig. 2 is also shown in Fig. 3, in which the equation approximately bisected the range of NDII at a given CWC. Thus, some error in the regression between CWC and NDII may have been caused by variation of soil conditions, in which case the relationship between CWC and NDII may be improved for a given site defined by incorporating additional soil information. But for global applications requiring CWC, the empirical relationship in Fig. 2 may be sufficient.

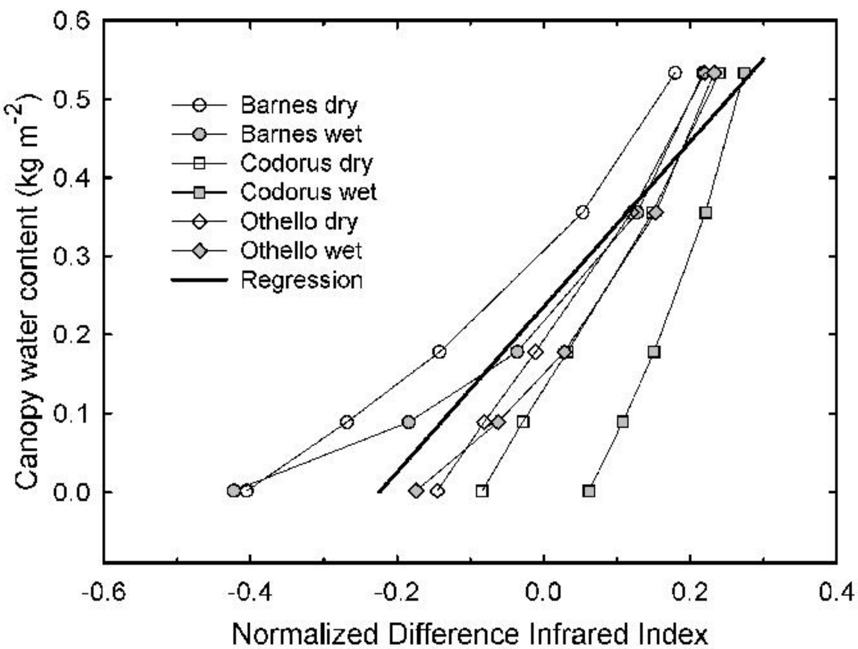

Fig.3. Comparisons of CWC and NDII from simulations using the Scattering by Arbitrarily Inclined Leaves (SAIL) model with three different soil types, both moist and dry. CWC was equal to the product of leaf water content (LWC) and leaf area index (LAI). The thick line is the regression equation from Fig. 2.

There were significant linear relationships between CWC and VWC for corn and soybean ($P < 0.0001$), which led to good linear relationships between NDII and VWC (Fig. 4). The linear relationships between CWC and VWC imply that the allometric β coefficient (exponent, Eq. 1) was equal to one. The theoretical value of β is 0.75 (Enquist & Niklas, 2002; Niklas & Enquist, 2002), so there may have been an error with the assumption that the allometric relationship between stem and leaves for water content would be the same as for dry matter. Another potential reason the observed relationship was linear is that the ranges in CWC and VWC were small compared to the variability of all vascular plants, so the allometric equations would approximate a line in this study. However, Zhang and Kondragunta (2006) found linear allometric relationships between foliar dry mass and above-ground dry mass using data from the Forestry Inventory Analysis program of the USDA Forest Service. The α coefficient (slope, Eq.

1) is very different between corn and soybean, so relationships between NDII and VWC will need to be separately determined for each land cover type.

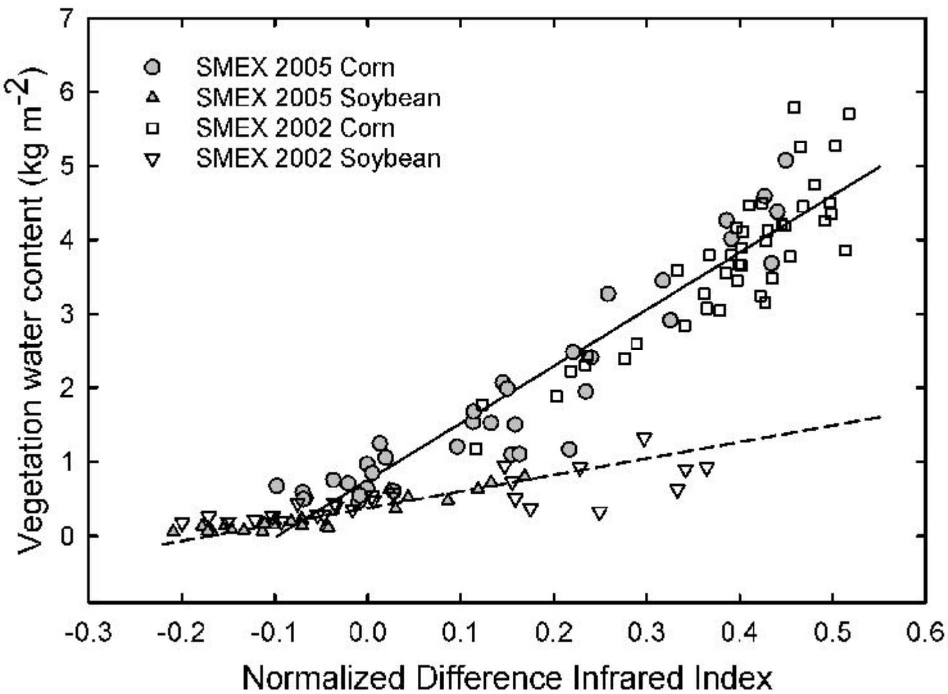

Fig.4. Vegetation water contents (VWC) of corn and soybean from the Soil Moisture Experiment 2002 (Jackson et al., 2004) and the Soil Moisture Experiment 2005 (Yilmaz et al., 2008b). VWC is the sum of stem water content and canopy water content.

3.2 MODIS and WindSat comparison

The MODIS retrieved VWC varied for the three WindSat footprints for each year (Fig. 5). The differences among the footprints were due to differences in land cover (Table 2) and perhaps soil type. The differences in VWC among years for each footprint in May were due to differences in the dates of crop emergence (Table 2). During the month of June, there is a large increase in VWC for each year, corresponding to the large increase in LAI of corn (Fig. 5); among years, differences in the growth rate of corn may have been caused by differences of insolation, air temperature and precipitation.

In the beginning of May, the WindSat retrieved VWC values for central Iowa were lower than other regions in the state, particularly compared to south-central Iowa (Fig. 6a). Central Iowa is part of the Des Moines Lobe landform, where corn and soybean crops represented 76% of the total area based on the USDA-NASS Cropland Data Layer (Mueller & Seffrin, 2006). In contrast, south-central Iowa had 49% of the area in grasses, pasture and woodland, which emerged earlier in the year. By the beginning of August, most of Iowa had VWC greater than 4 kg m^{-2} (Fig. 6b). WindSat-retrieved VWC for the three footprints showed differences among each other and among years (Fig. 7). There was more variation among years than among the three footprints, which may have been caused by general meteorological conditions such as temperature and precipitation.

Table 2. Fractional amounts of the different land cover classes from the USDA National Agricultural Statistics Service Cropland Data Layer for three WindSat footprints. Fractional emergence by 1-7 May for each year indicates variation in planting dates. From independent analyses during SMEX05, the classification accuracy was 92% for all classes (Yilmaz et al., 2008b). The center-point's latitude for the WindSat footprints was 42.0322° N.

	Emergence (% of	Longitude		
2003	fields) by 1-7 May [1]	94.2299° W	93.7093° W	93.1887° W
Corn	12	0.52	0.45	0.46
Soybean	2	0.36	0.34	0.38
Pasture	-	0.10	0.16	0.13
Woodland	-	0.01	0.03	0.00
2004				
Corn	36	0.46	0.43	0.44
Soybean	4	0.44	0.35	0.39
Pasture	-	0.06	0.12	0.13
Woodland	-	0.03	0.04	0.01
2005				
Corn	15	0.43	0.44	0.49
Soybean	0	0.42	0.34	0.37
Pasture	-	0.11	0.10	0.07
Woodland	-	0.04	0.09	0.04

[1] From the USDA National Agricultural Statistics Service, Weekly Weather and Crop Bulletin State Stories, Washington DC (http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1574, last accessed 28 March 2011).

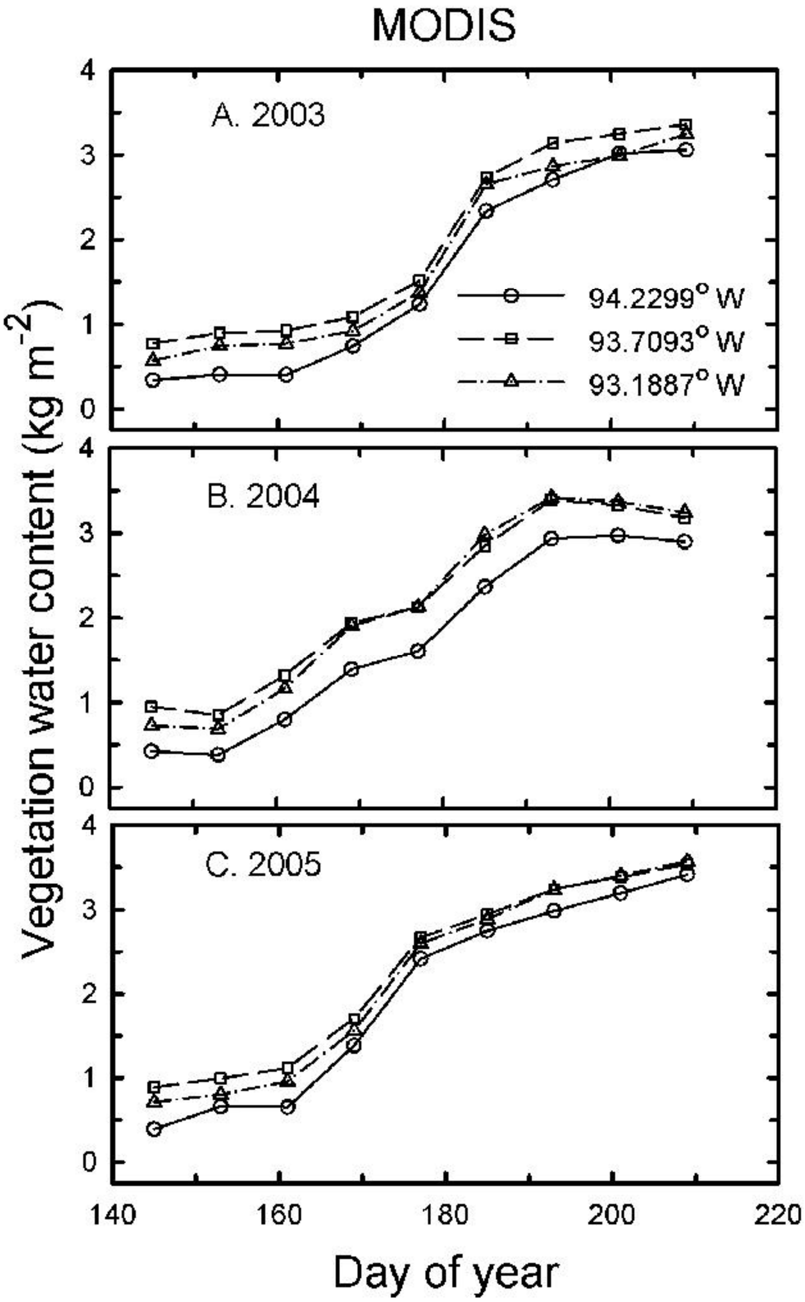

Fig. 5. MODIS VWC for three WindSat footprints in central Iowa for (A) 2003, (B) 2004, and (C) 2005. Differences among footprints and among years are related to crop planting and emergence, which depends on temperatures and precipitation. Yearday 140 is 21 May and 220 is 9 August.

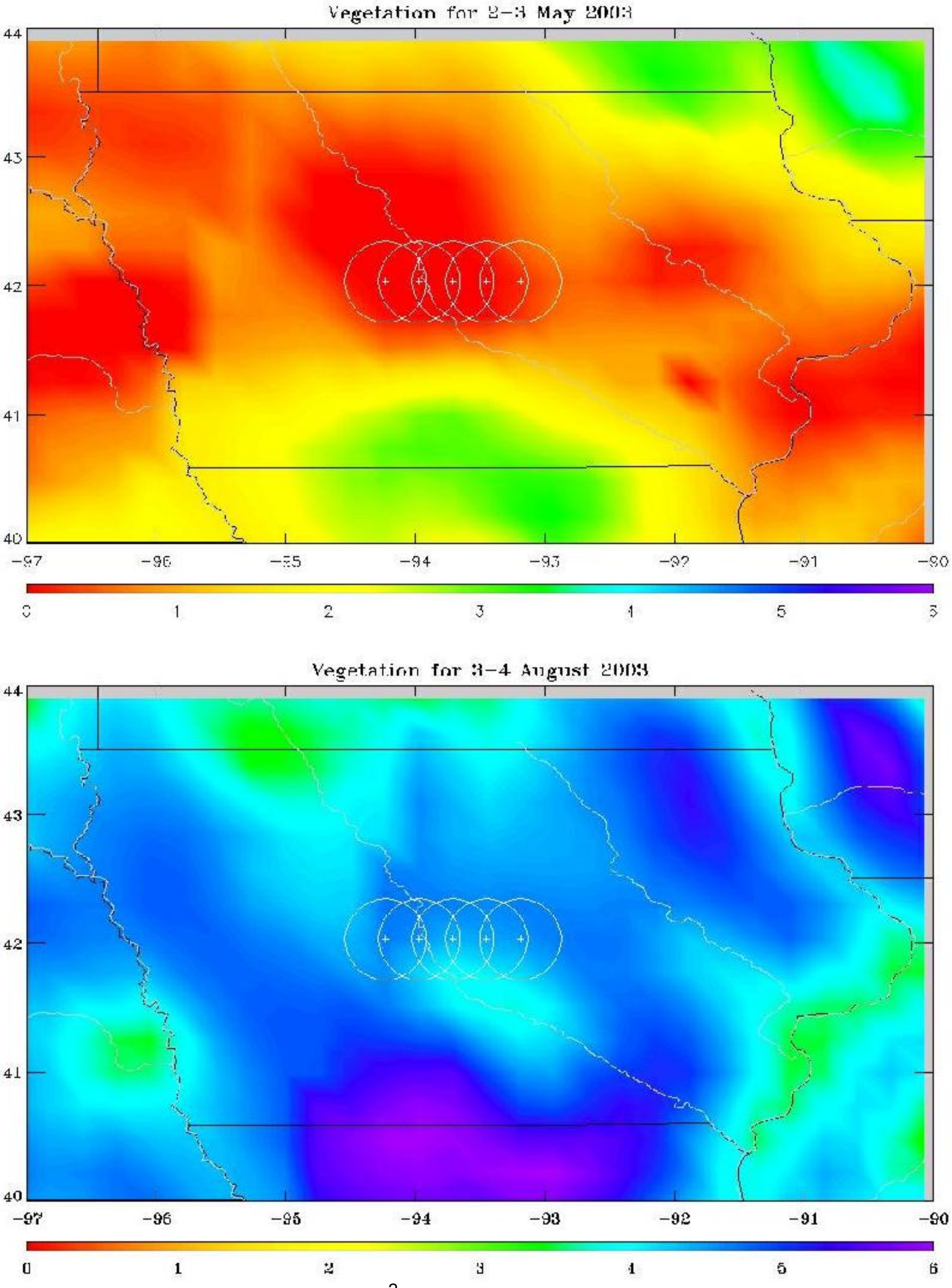

Fig. 6. WindSat retrievals of VWC (kg m^{-2}) for the beginnings of (A) May and (B) August. WindSat footprints are overlapping (white circles). Non-overlapping footprints were acquired using the first, third and fifth swaths shown above. The radius of the WindSat footprint for soil moisture retrievals is about 30 km.

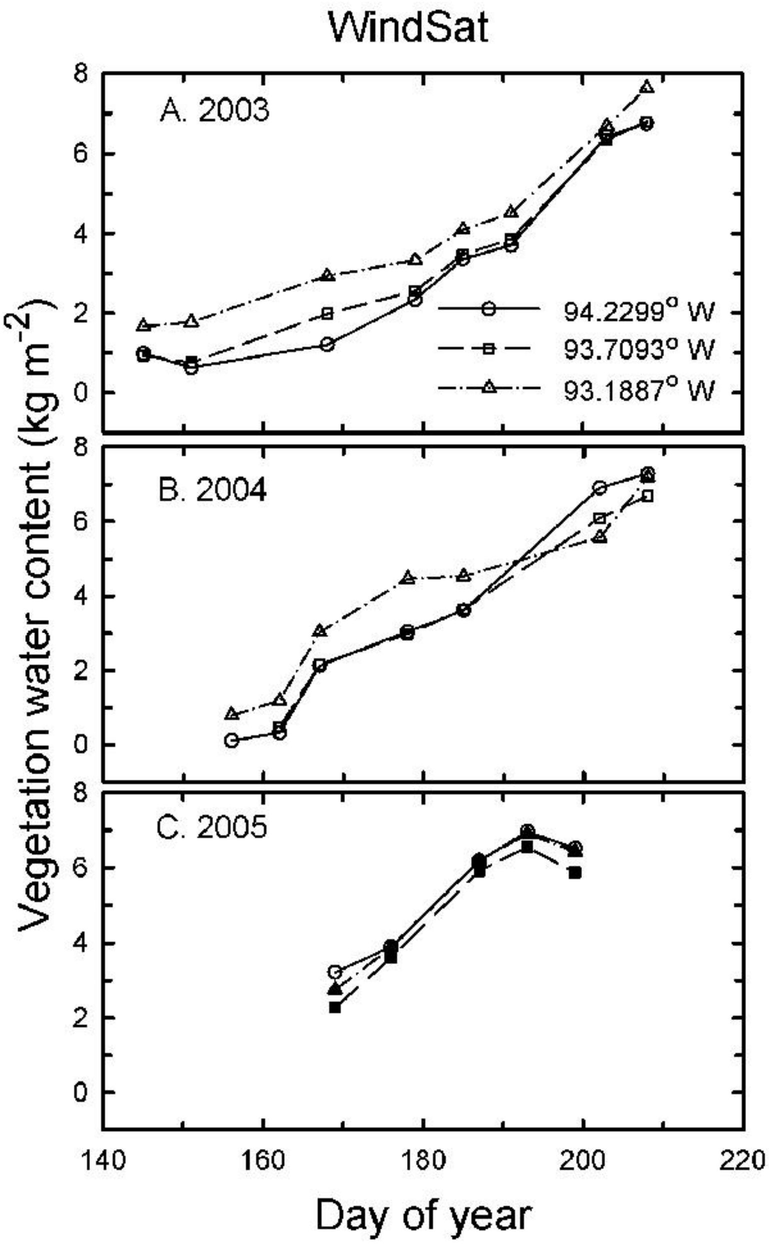

Fig. 7. WindSat retrieved VWC for three non-overlapping footprints in central Iowa for (A) 2003, (B) 2004, and (C) 2005. Yearday 140 is 21 May and 220 is 9 August.

VWC of each field site were averaged for the 4 different sample periods during SMEX05, with the averages weighted with the proportions of corn, soybean, pasture and woodland from the Cropland Data Layer (Table 2). Variances of VWC were calculated from the component variances and proportional area weights (Sokal and Rohlf, 1995). The large standard deviations for the SMEX05 data (Fig. 8) were caused largely by: (1) only 21 field sites, and (2) different planting dates for corn. Because MODIS VWC was calibrated in part with the SMEX05 data, it was expected that MODIS VWC would be similar to field VWC (Fig. 8). Indeed, MODIS VWC may be closer to the true mean of VWC for the footprint, because: (1) the differences in planting date for corn were included in NDII, and (2) there was a large number of MODIS pixels compared to the number of field sites. WindSat VWC retrievals were independent of the field data and the resulting VWC were much larger than either MODIS VWC or field VWC (Fig. 8).

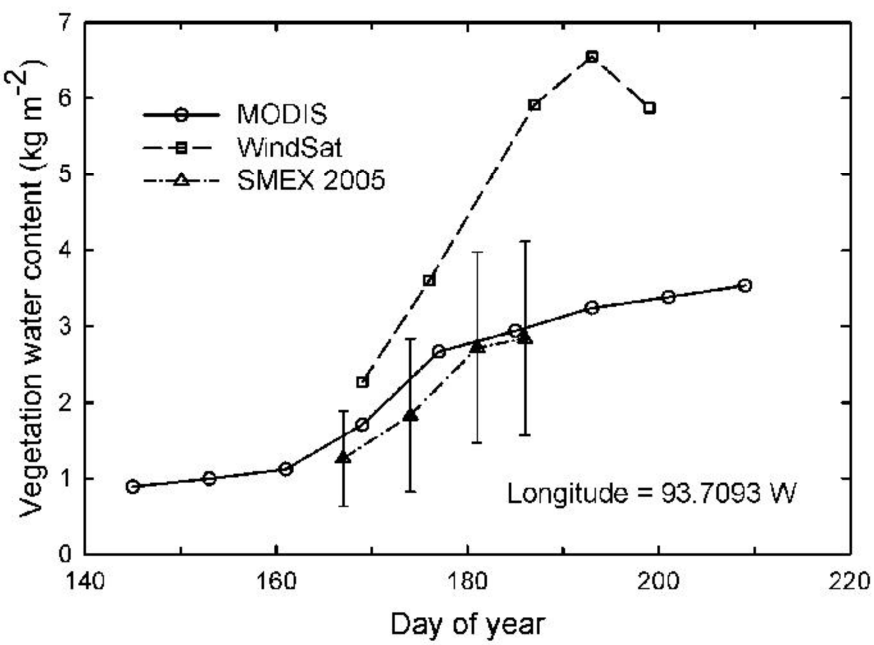

Fig. 8. Comparison of VWC from WindSat, MODIS, and field data for 2005 over the center WindSat footprint. The error bars for the field data acquired during SMEX 2005 are ± 1 standard deviation.

WindSat VWC was significantly correlated with MODIS VWC, with $P < 0.0001$ (Fig. 9). This is important because there was no inter-calibration between MODIS and WindSat VWC estimates. The regression intercept was not significantly different from zero with $P = 0.25$ (Fig. 9),. The slope of the regression equation indicated that on average, WindSat VWC was about two-times greater than MODIS VWC. This slope may be attributed to the estimated b parameter in Equation 4. Therefore, if we assume that the MODIS VWC was well calibrated for corn and soybean in central Iowa (Fig. 8), we can then use these data to adjust the b parameter (Eq. 4) to make the slope of the WindSat-MODIS comparison (Fig. 9) equal to one. Adjustments for VWC retrieval from passive-microwave data at a satellite footprint scale may be necessary for different land cover types.

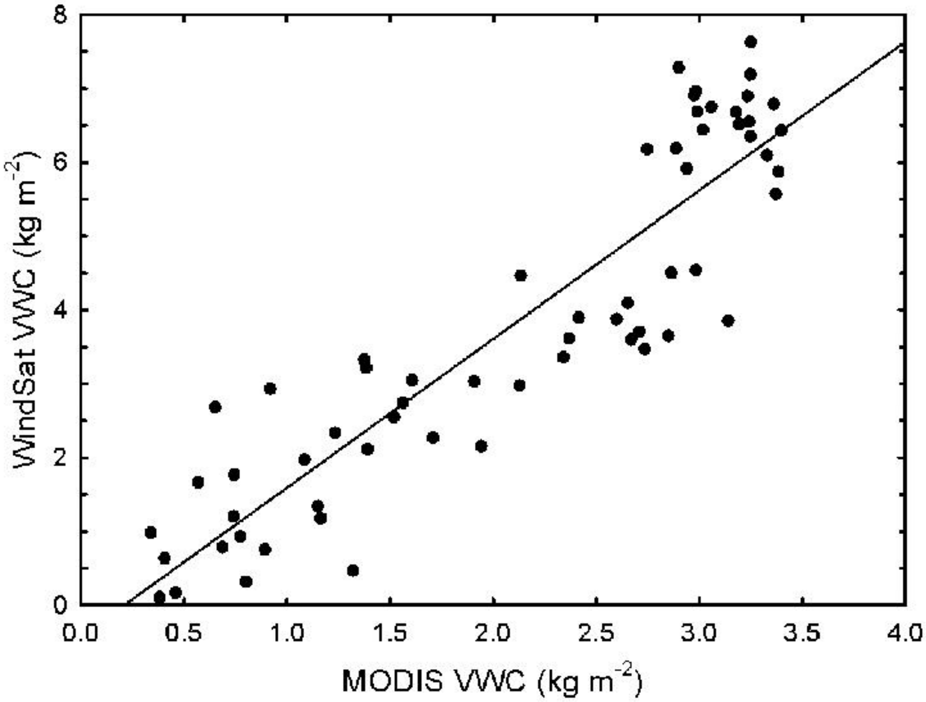

Fig. 9. Comparison of MODIS and WindSat VWC retrievals over central Iowa for 2003 to 2005. The solid line shows a linear regression of WindSat VWC = -0.4 + 2.01 MODIS VWC, with an RMSE of 0.96, and an R^2 = 0.82.

From many studies, red/near-infrared vegetation indices are not as useful for estimating VWC as foliar-water indices for CWC, in part because red/near-infrared indices saturate at much lower LAI (Roberts et al., 1998, 2004; Sims & Gamon, 2003). The MODIS LAI data product (Tan et al., 2005) could be used instead of foliar-water indices to develop allometric equations for VWC. However, independent evaluations of the previous Collection 4 MODIS LAI data product arrived at absolute values of LAI error greater than 1.0 (Aragão et al., 2005; Verbyla, 2005; Hill et al., 2006; Rizzi et al., 2006). With an RMSE = 0.09 kg m^{-2} (Fig. 2), compared to the median value of LWC (0.2 kg m^{-2}), the uncertainty in LAI from NDII is about ± 0.46, with a potential range from ± 0.28 to ± 0.83. Sims & Gamon (2003) and Hunt et al. (2009) suggested that spectral indices for canopy water content may provide good estimates of LAI.

The VWC retrievals from WindSat and MODIS each have uncertainties, but the standard error of VWC from the MODIS retrieval for a WindSat footprint should be low because about 2800 1-km^2 MODIS pixels were averaged over the much larger WindSat footprint. Furthermore, the topography of central Iowa is relatively flat and the land cover is relatively simple, mostly corn and soybean, for which VWC is relatively easy to measure in the field. The linear correlation between VWC from WindSat and MODIS indicates that a combined sensor approach is feasible.

4. Conclusions and Significance

VWC retrievals from MODIS and WindSat were consistent with each other. Estimation of VWC with MODIS is based both on theoretical grounds (e.g. allometric relationships between stem and canopy water contents) and practical grounds (e.g. NDII saturates at higher LAI than does NDVI). The Visible Infrared Imager Radiometer Suite (VIIRS) is expected to have a band at 1.61 μm wavelength with a pixel resolution of 375 m (Lee et al., 2006), so estimates of CWC at a somewhat higher spatial resolution should continue in the future.

A problem with passive-microwave radiometers is large footprints, which are sensitive to the heterogeneity in VWC (Crow et al., 2005; Davenport et al., 2008). Moreover, the footprint areas are different at each frequency and the footprint center points will shift with successive orbits on the same satellite path (Gaiser et al., 2004). MODIS foliar-water indices will potentially reduce the scaling errors of microwave soil moisture retrievals over heterogeneous scenes by providing ancillary VWC at finer spatial resolution.

With VWC estimated from MODIS or other satellite data, retrievals of soil moisture from passive microwave radiometers are expected to be more accurate because fewer variables must be simultaneously determined. Increased accuracies of soil moisture and VWC retrievals are important in the development of long-term multi-sensor data records for climatic analysis (Owe et al., 2008; Liu et al., 2009). Assimilation of AMSR-E soil moisture retrievals added significant value for estimating impacts of drought on agricultural production (Bolten et al., 2010). Based on MODIS and the Advanced Very High Resolution Radiometer 3 (AVHRR/3), long-term multi-sensor data records of foliar-water indices can be used synergistically with the soil moisture data products for accurate environmental data records.

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